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Automatic Classification of Power Quality Disturbances Using Hidden Markov Models

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Abstract— **In this paper, the Discrete Wavelet Transform is implemented for detection of ten types of the power quality (PQ) disturbance signals. Further, four features of the single as well as the combined PQ signals disturbances are extracted from these wavelet transforms coefficients. The features are plotted w.r,t their decomposition levels in order to distinguish the disturbances with their feature value. Moreover, these features are again fed as inputs Hidden Markov Models (HMMs) classifiers to classify the disturbances by the calculating the classification accuracy (CA).**

Keywords- **Power Quality (PQ); Hidden Markov Models (HMMs); classification accuracy (CA); Wavelet Transform (WT)**

I. INTRODUCTION

The Power Quality has emerging a pressing concern due to the continuous increasing of the number of distributing loads of the public sectors. The disturbances in their loads create the deviation of voltage and current waveform from the ideal that declines the performance and the lifespan of the equipment's [1] in terms of power quality (PQ). The decrease in voltage signal is identified as sag and similarly the opposite called as swell. The electronically controlled capacitor switched operation creates the transient and similarly multiple integral frequency known as harmonics, notch are also observed in solid state power electronics instruments. In addition to these PQ disturbances, the spike is introduced due to the lightening, and the arc furnace operation conceives the flicker. In order to enhance the PQ with mitigating these disturbances, the signal patterns must be discriminate first. As a result, the research has been directed towards the automatic classification of the disturbances in deregulated power system where the power quality is one of the important discriminating factors for electing different suppliers [2]. However, the existing automatic recognition methods for time series pattern need enhancement with the efficiency and reliability.

The several authors has introduced different methodology such as the fast operated Fourier transform (FT), the short-time Fourier transform (STFT), the wavelet transform (WT), the Neural Network, the Fuzzy logic, the S-transform, Kalman filter have been used over past year [3]-[10]. The STFT is suitable for only steady state disturbances like sag and swell but the transient signals including notch cannot analyzed due to the fixed window[11]-[13].The time frequency resolution of the signals in STFT analysis is limited by Heisenberg-Gabor inequality. The Multiresolution Analysis (MRA) based Wavelet Transform (WT) is extensively used for characterization of non-stationary signal which provides the time frequency relationship by convolving the dilated and translated version of the wavelet with signal. The important features can be extracted with these coefficients in order to reduce the data size for classification. The feature extraction is also plays a crucial rule for proper classification of PQ disturbances. In other words the feature extraction is a process of extraction of minimum information from a phenomena which provides maximum differentiation among phoneme classes [14]-[18].

However, researcher has been focus on automatic detection and classification of power quality disturbances with Artificial Neural Network (ANN), and Fuzzy logic etc. has been used applied but they are not robust like the data mining based classifiers [19]-[22]. The ANN requires retraining when a new phenomenon is added and becomes tedious when a huge number of disturbance classes are present. So the Hidden Markov Models (HMMs) has been introduced to classify the large number of phenomena [22-25].

The paper is organized as follows. Section II of the paper describes the brief theory of the DWT for detection and the Section III deals with the feature extraction process and the two types of classifiers used in computing the classification accuracy. The brief description about the classification approach is given in Section-IV. The Section V has carried out the process of detection using the theory described in the section II. The Section VI has used the features extraction methods described in section III. Similarly the Section VII has been given with classification result. Finally, the Section VIII has been provided with the concluding remarks.

II. DETECTION USING DESCRETE WAVELET TRANSFORM

The detection of the PQ disturbance is carried out with the widely used simple DWT decomposer.

Discrete Wavelet Transform

The discrete wavelet transform (DWT) is one of the good techniques used to decompose a discretized signal into different resolution levels. In the DWT decomposition, the wavelet function generates the detail coefficients of the decomposed signal whereas the scaling function generates the approximation coefficients of the decomposed signal. The expression for DWT [15]

$$DWT(m,k) = \frac{1}{\sqrt{a_0^m}} \sum_n x(n) g\left(\frac{k - nb_0 a_0^m}{a_0^m}\right) \qquad (1)$$

where "k" is an integer that used to refer the sample with the mother wavelet "g". Similarly, scaling parameter $a = a_0^m$ and translation parameter $b = nb_0 a_0^m$. Both 'a and b' vary in the discrete manner. At the first level decomposition, the time signal ' $S(n)$ ' decomposed in to the detailed ' $d_1(n)$ ' and the smoothed ' $c_1(n)$ ' through quadrature mirror filter i.e the high pass 'h(n)' and low pass filters 'l(n)'. Thus the smooth version ' $c_1(n)$ ' contains lower frequency components than the detail version ' $d_1(n)$ '. Mathematically, they can be represent as

$$c_1(n) = \sum_k h(k - 2n) c_0(k) \qquad (2)$$

$$d_1(n) = \sum_k g(k - 2n) c_0(k) \qquad (3)$$

where, ' $c_0(k)$ ' is the discretized time signal of the original signal(sampled version of ' $S(n)$ '). The number of samples reduced to half as the output after each of decomposition, is down sampled by a factor of '2'. Moreover, these approximation coefficients are further fed to the quadrature mirror filters in order to iterate the process. The 'Quadrature mirror filters' which are related by the equation [18],[12]

$$h[L-1-n] = (-1)^n l(n) \qquad (4)$$

where, L is the filter length. The basic block diagram of the decomposition is given in Fig2.

III. THEORY OF THE FEATURE EXTRACTION AND CLASSIFICATION

Feature extraction

The PQ disturbance signals decomposed with DWT decomposition and with the resulted approximations and details at each of the decomposition levels four features are extracted using the given equations [26],[27].

Energy $$ED_i = \frac{1}{N} \sum_{j=1}^{N} \left|D_{ij}\right|^2 \qquad (5)$$

Mean $$\mu_i = \frac{1}{N} \sum_{j=1}^{N} D_{ij} \qquad (6)$$

Standard deviation $$\sigma_i = \left(\frac{1}{N} \sum_{j=1}^{N} \left(D_{ij} - \mu_i\right)^2\right)^{1/2} \qquad (7)$$

Entropy $$ENT_i = -\sum_{j=1}^{N} D_{ij}^2 \log\left(D_{ij}^2\right) \qquad (8)$$

where i=1, 2, 3……………………l. (decomposition level number) and N is the number of samples in each decomposed dataset. The disturbance signals such as like sag, swell, sag with harmonic and swell with harmonic are classified using the standard deviation [11] but all type of disturbances are not properly distinguished. So these extracted features are further fed as input to the different classification algorithm to reduce the computational burden of the raw data. The classification algorithms are discussed in the next section.

IV. CLASSIFICATION APPROACH

The improvement of quality of power is simulated by the proper recognition of the disturbances presented in system. The recognition rate has enhanced by the implementation of the automated classifiers .There are 20900 signals are synthesized for all ten types of disturbances of each with 28 features of 7^{th} level of DWT decomposition. At the each level of decomposition, each outcome is normalized with the maximum value to formulate the dataset. The basic classification operation is divided as training and testing for which 60% of the dataset are fed as the training data to build a training model and the rest 40% of data are implement for testing purpose.

Artificial Neural Network (ANN)

The design of neural network I the real world is complex. The ANN is iterative process. The inter-related skeletal steps are present subsequently.

Step 1: Determination of the availability of measurements (input) or feature (pre-processed) data.

Step 2: Consideration of the availability and quantity of training and the test data.
Step 3: Considering the availability of suitable and known ANN system structures.
Step 4: Developing an ANN simulation.
Step 5: Training of the ANN system.
Step 6: Simulating the ANN system performance-using test set.
Step 7: Iterating until the desired output is gained.

A. ANN

An ANN module consists of neurons and their connections form a network like structure. The basic element of ANN is called neuron. The input of a neuron is generally an input column-vector of a $x = [x(1), x(2).......x(i)]^T$ pre-processed data. Where, the nth element of the input vector, ' x(n)', is connected to a neuron 'p' by a weight factor w(p, i) . This weight factor then forms a weight vector for the neuron 'p', $w_p = [m(p,1)............m(p,i)]$. The output of the neuron is a linear combination the weight vector 'w_p', with of the input vector 'x' as shown in (9)

$$u_p = wx^T = \sum w(p,i)x(i) \; for \; i = 1...I \qquad (9)$$

The data path is constructed with three layers, one hidden layer and one for the output layer which is connected in the traditional feed-forward architecture with input layer. The inputs come directly from the data bus into the neurons at the hidden layer. The structure of this MFNN is 3-3-1. One disturbance class and other, without disturbance class (pure sine wave) are considered. The classification accuracy is found out according to the equation as given below.

$$\text{Classification Accuracy (\%)} = \frac{No.of\ samples\ correctly\ classified}{Total\ no.of\ samples\ in\ the\ data\ set} \times 100 \qquad (10)$$

B. HMM

After the disturbances are decomposed, the features vectors are extracted. The HMMs is applied to feature vector in order to determine the maximum likelihood in the data set. The HMM, extension of the Markov model in which the stochastic process is not directly observable through another set of stochastic processes. However, an HMM can be defined as λ = (N, M, π, A, B) where the parameter N denotes the number of states of the model, M is the number of distinct observation symbols per state, π is the initial state distribution vector, similarly , A denotes the state transition probability and finally B is observation probability matrices respectively. A discrete HMM is explained in [23],[24] through the model of individual states.

Like other classifiers, the HMMs operation is partitioned into the training and the testing stage of dataset. The HMM training model uses both continuous and discrete density modelling and also employs the Baum-Welch algorithm to construct the HMMs [25]. Starting with a very simple prototype system, the HMMs are repeatedly modified and re-estimated until the required level of model complexity and performance is reached. In this study, ten different Figures and Tables HMMs are trained for ten disturbance classes. For this classification process, the logarithmic probability of each model output is determined for the unknown input signals. In order to develop a proper HMM, the selection of the optimum number of state and the density function are very important but there is no explicit rule for the selection of these factors except the application type and the parameters. In this work, three states are selected to stipulate the output with the Gaussian mixtures function. The prior distribution is used over the state transition to favour the transitions in order to stay in the same state. The prior is multiplied by the likelihood function and then normalized according to the Bayes theorem. The CA depends on the number of matching of the testing with the trained model using the equation (10)

V. LOCALIZATION RESULT

TABLE.1 Power signal Class labels

PQ signals	Class labels
Sag	C1
Swell	C2
Interruption	C3
Oscillatory transient	C4
Flicker	C5
Harmonic	C6
Sag+harmonics	C7
Swell+harmonics	C8
Notch	C9
Spike	C10

The theory described in section II has been used to calculate the approximate and detailed coefficients at four levels using the DWT for all the ten PQ disturbance signals [18].

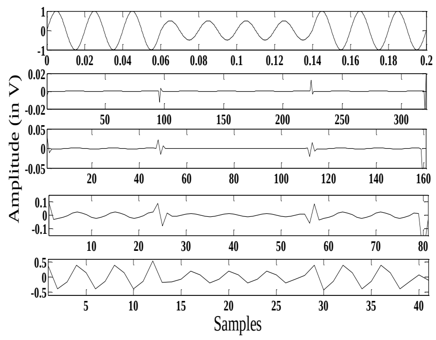

Figure 2. DWT decomposition of pure sine wave with sag

There are ten types of disturbances are simulated with 3.2 kHz sampling frequency and fundamental frequency of 50 Hz. The Table.1 shows the class levels given to PQ signals. The MATLAB code along with the wavelet decomposition algorithm has been used for the purpose of detection. The decomposition levels and the corresponding description for the sine wave with sag, sine wave with swell, and sag with harmonics and swell with harmonics are shown in Fig.2 to Fig.5 respectively. From, Fig.2-Fig,5 it is observed that the point of disturbances are clearly identified even at the finer decomposition levels.

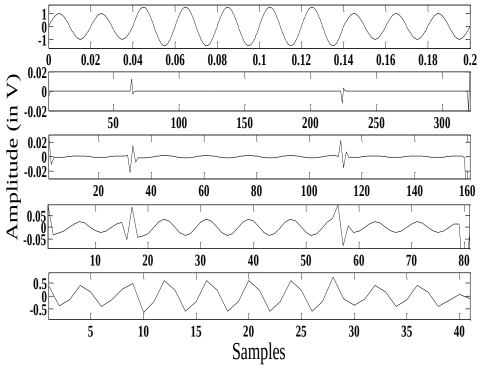

Figure 3. DWT decomposition of pure sine wave with swell

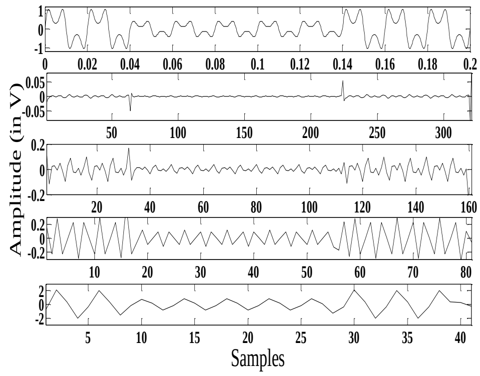

Figure 4. DWT decomposition of sag with harmonic

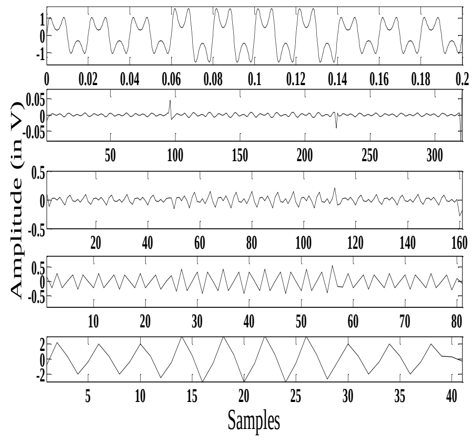

Figure 5. DWT decomposition of swell with harmonic

VI. FEATURE EXTRACTION RESULT

In this paper, the three features namely the energy; the entropy and the standard deviation of ten PQDs along with the normal sine wave are extracted with the DWT coefficients. The standard deviation of different decomposition levels are plotted with DWT in Fig. 6(a) and 6(b). The horizontal axis represents the level of decomposition and the y-axis represents the magnitude. At higher frequency zone in both the cases the oscillatory voltage signal, sag signal with harmonic and swell signal with harmonic are differentiated which are shown in Fig.6(a) and (b) . The peak of the standard deviation curve in notch is higher than the spike. Overall, the peak of the standard deviation curve of notch and spike deviate from others in proportional their magnitude and duration of disturbance, shown in Fig. 6(b).

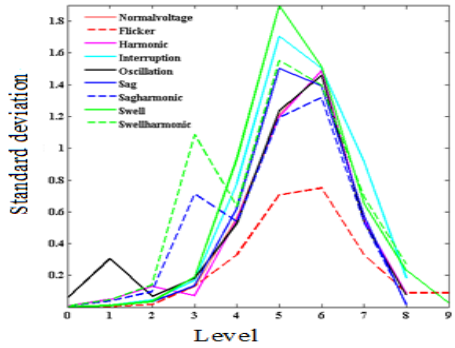

Figure. 6(a).STD curve in DWT

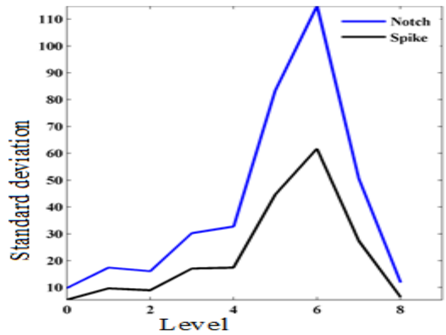

Figure. 6(b).STD curve in DWT

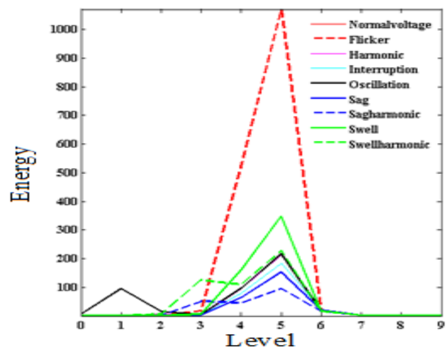

Figure 7(a). Energy curve in DWT

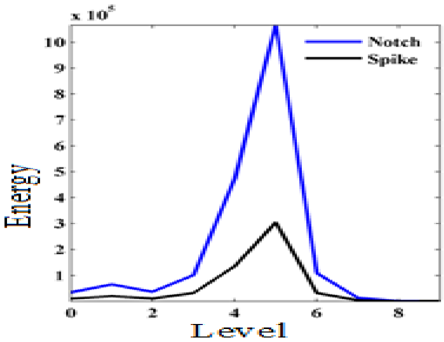

Figure. 7(b).Energy curve in DWT

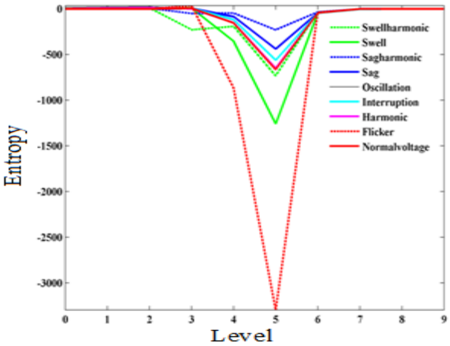

Figure 8 (a). Entropy curve in DWT

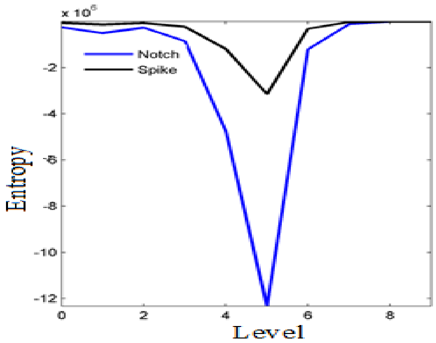

Fig.8 (b). Entropy curve in DWT

The energy at different levels are plotted using extracted from DWT coefficients shown in Fig.7.(a) and (b). For DWT, the oscillation, the sag with harmonic and also the swell with harmonic signals are differentiated from other signals at the higher frequency zone. The harmonic signals are considered as stationary in power system. The magnitude of harmonic signal and normal voltage energy curve are same using DWT. Similarly, the notch possesses high energy level than others. The energy deviation of the notch and the spike are more prominent than the others as deviations are more which shown in Fig.7 (b).

Similarly the entropy curves are also plotted against the levels present in Fig.8. (a),(b). But all the signals are not clearly classified with the feature plot. Hence, classifiers such as MLP and HMM are implemented to make a proper discrimination among the PQ phenomena.

VII. RESULTS OF THE CLASSIFICATION

TABLE.2 CA (%) of pure signals

Signal class	%CA in MLP	%CA in HMM
C1	67.42	75.21
C2	63.54	99.56
C3	60.45	0
C4	65.07	98.36
C5	73.40	93.3
C6	57.32	47.61
C7	68.17	43.32
C8	70.21	73.60
C9	69.38	100
C10	69.76	98.33
Total	67.38	72.92

TABLE.3 CA (%) of signals with 20dB noise

Signal class	%CA in MLP	%CA in HMM
C1	61.43	93.04
C2	60.44	91.03
C3	61.58	0
C4	54.27	100
C5	62.57	80.74
C6	58.59	1.07
C7	56.98	34.40
C8	60.12	55.94
C9	57.01	93.03
C10	58.54	91.07
Total	57.02	61.03

TABLE.4 CA (%) of signals with 30dB noise

Signal class	%CA in MLP	%CA in HMM
C1	62.86	94.78
C2	61.93	84.65
C3	62.05	0
C4	58.18	100
C5	59.26	77.63
C6	63.52	1.71
C7	60.14	47.78
C8	55.50	45.64
C9	58.45	99.18
C10	59.62	92.21
Total	59.05	64.35

The total 28090 numbers of signals are simulated for the feature extraction and each of the signals are fed for decomposition up to ninth finer levels as a result total 27*28090 featured matrix is formed. For each of the dataset, 60% of the data are treated as training data and rest 40% of data are fed to test the unknown signals.

The two techniques are applied to classify different types of PQ disturbances in order to discriminate the classifiers with their efficiency as well the inefficacy.

The classification accuracy of pure PQ signal is compared in the Table.2. Except the slow disturbances like interruption and harmonic, all other disturbances are classified efficiently than the MLP. Here also, HMMs with 5 states is applied. The overall classification accuracy of HMMs is more in case of MLP. In order to get the efficacy of the proposed HMM with large class data, the signals are classified in noisy environment. The pure PQ disturbances are added with noise of SNR 20db and 30db in order to get the disturbances in noise environments. The aforementioned features are extracted and the % CA is shown in Table.3 and Table.4.

These above Tables (Table.3-Table.5) provide the classification accuracy computed using the two classifiers with and without noise. The same data sets are fed to the two classifiers. Moreover, Tables has been demonstrated that the %CA values of such huge data set are good with the HMMs classifier as compare to the ANN based MLP. The fast disturbances affect the system more than the slow disturbances. Moreover, the automated HMMs classifier discriminates the fast disturbance perfectly. The fast disturbances are also discriminates from the slow disturbance. As overall accuracy get reduces as the interruption, harmonic signals are not classify. In spite of this the HMMs provides better %CA with large class of disturbance.

VIII. CONCLUSION

The identification of PQ disturbance signals are presents with the application of DWT. The features extracted from DWT decomposition are fed two automatic classifiers based on artificial intelligence which approach provide a novel scope for PQ analysis. The CA of the HMMs classifiers based on maximum likelihood is presented in this paper to manifest the better recognition rate. The recognition rate and performance of the HMMs classifier is better than the traditional MPL. In spite of the low %CA of slow disturbance the disturbances are classified properly in HMMs. The HMMs provides discrimination between the slow and fast disturbance which helps the system protect from the dangerous fast disturbance like transients. So, the HMMs a good classifier for the modern complicated power system with uncommon disturbance.

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